From Words to Rewards: Leveraging Natural Language for Reinforcement Learning

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Abstract

We explore the use of natural language for specifying rewards in Reinforcement Learning with Human Feedback (RLHF). Human language provides rich and nuanced information, yet most existing approaches rely on simplistic preference data or constrain the text structure. In contrast, we harness the power of Large Language Models (LLMs) to fully leverage natural text to efficiently train a reward model. Our empirical studies with human participants highlight the remarkable benefits of this strategy. Even with minimal human interaction, our method of integrating text feedback with LLMs accurately approximates the reward function and leads to significant performance gains.

1 Introduction

Reinforcement Learning (RL) [1] is a powerful framework for solving complex decision-making problems by training agents to maximize cumulative rewards through interactions with an environment. Central to the RL paradigm is the concept of a reward function, which provides the agent with feedback on its actions and guides its learning process. However, defining an appropriate reward function in real-world applications is a significant challenge [2]. This limitation hinders the deployment of RL in many practical scenarios where the specification of a reward function is ambiguous or subjective. To address these challenges, Reinforcement Learning from Human Feedback (RLHF) [3] has emerged as a promising approach. Rather than relying on predefined reward functions, RLHF derives a reward signal directly from human input, ensuring it better reflects human values and intentions. This strategy has been especially effective in domains where human judgment is crucial for determining task success.

While most RLHF approaches rely on comparing or ranking trajectories, humans naturally communicate intent through more nuanced textual descriptions [4]. Shifting from comparison-based feedback to textual input would allow for a richer expression of underlying goals [5]. However, for such text-based feedback to be useful in RL, it must be effectively translated into a suitable reward model for planning. In this paper, we introduce a novel approach for learning reward models from natural language feedback. We bridge this gap by employing Large Language Models (LLM) to map expressive human text into structured representations which we use to update a reward model. This allows the reward model to capture the context and subtleties of human preferences more effectively, leading to more robust and adaptable RL agents. Our contributions are as follows:

- We propose an in-context learning approach using LLMs to seamlessly and robustly map human textual feedback into state-level rewards for reward model training.
- We incorporate our reward modeling approach into a RLHF framework and systematically validate its performance in a gridworld environment through experiments with 26 human participants.
- We investigate how human feedback, compared to ground-truth environment feedback, proactively guides agents towards unexplored high-reward states, boosting performance in cases with low interaction budget.

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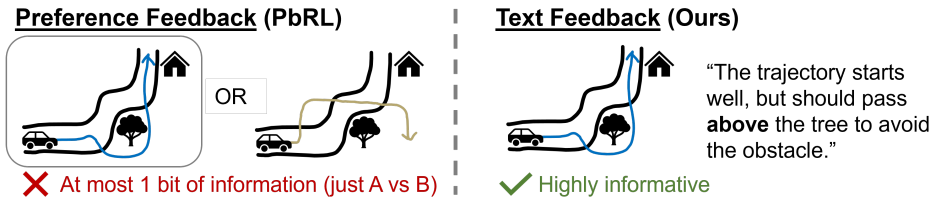


Figure 1: Traditional RLHF relies on binary preferences between trajectories, providing at most one bit of information per query. We propose using natural language feedback, which is both human-interpretable and significantly more informative, enabling reward learning with less interactions.

- We extend our framework to continuous environments, demonstrating task success with as few as 10 human text feedback instances while avoiding common reward modeling challenges.

2 Related Work

Preference Based Reinforcement Learning Traditional RL relies on explicit reward functions to drive the learning process. When the reward function is not known or difficult to construct, one may collect human feedback to model the reward. In Preference Based Reinforcement Learning (PbRL) [6, 3], human oracles provide their preferences between pairs of trajectories. These preferences are used to train a reward model, enabling the deployment of standard RL algorithms to find the optimal policy. Unfortunately, as depicted in Figure 1, relying solely on comparisons misses out on valuable information about finer details of the reward [7, 8]. We propose using natural language feedback to overcome this limitation.

Learning from Natural Human Feedback A natural way for humans to interact and express their intentions is through text. Consequently, there is much interest in leveraging natural language in RL. One common strategy is to map natural language instructions to trajectories or features. To achieve this mapping, previous works limit the instructions to a finite set [9–12], or force a specific sentence structure, e.g., "Go to X" [13]. These restrictions simplify the mapping process, but, unlike our algorithm, they also limit the flexibility of the language used. Another approach relies on pre-trained valence analyzers [14], which translate text feedback into a sentiment score. At each iteration, the sentiment score of the whole text drives the Bayesian update of the reward model [15]. A single sentiment score may not capture all nuances in human text, e.g., "*the start is good, but the end is bad*."

Language Models in Reinforcement Learning LLMs have recently emerged as powerful tools for natural language processing, providing novel approaches in the field of RL. One direction treats pretrained LLMs as proxies for reward signals, directly querying whether an outcome satisfies a language description of an objective [16]. While promising, this binary feedback is limited in expressivity, an inherent information bottleneck that our method aims to overcome. Another approach harnesses LLMs' general knowledge to provide common sense priors [17, 18, 8] that bias agent actions, for example, identifying hazardous states from metadata [19]. These methods complement our approach, which aims to learn subjective human intentions that are unknown to LLMs. A third line of work employs LLMs to translate human text inputs into reward functions in the form of code. However, these algorithms generally rely on the existence of reward evaluation functions [20, 21] or human binary preference feedback [22] to judge the performance of the generated reward functions. They also depend on LLM-generated code snippets which may be incorrect [23] and unreliable [24].

Our approach takes a different route: we use LLMs to convert free-form human text feedback, which provides more nuanced evaluations than preference feedback, into training data for reward modeling. While [21] includes one experiment in which the author provides text feedback, our work expands on this direction, collecting data from independent human participants. Additionally, instead of relying on LLM-generated diversity to avoid local maxima, our method uses text feedback to guide exploration towards relevant states.

3 Problem Setting

In this paper, we consider an *agent* who interacts with an *environment* aiming to maximize an expected reward. We describe the interactions between the agent and the environment as an episodic Markov

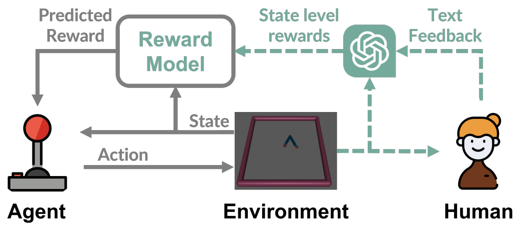


Figure 2: Block diagram of Reinforcement Learning from Human Text Feedback (RLHTF). The algorithm consists of two iterative phases: (1) learning a reward model (dashed lines) from state-level rewards derived by an LLM from human evaluations in natural language, and (2) policy learning (solid lines), where an agent is trained using standard RL algorithms that query the learned reward model.

Algorithm 1 RLHTF

Inputs: number of interactions N, landmarks, f_{LLM}
Initialize Policy π_0 and reward model $\widehat{r}_0$
for $i = 0$ **to** $N-1$ **do**
  Record trajectory following policy: $\mathbf{t}_i \leftarrow \pi_i$
  Query human for feedback: $\mathbf{f}_i \leftarrow \mathbf{t}_i$
  Encode context: $u_i \leftarrow (\mathbf{f}_i, \mathbf{t}_i, \text{landmarks})$
  Translate to state-reward pairs: $\{\mathbf{s}_o, R\} \leftarrow f_{\text{LLM}}(u_i)$
  Update reward model: $\widehat{r}_{i+1} \leftarrow \text{rew\_update}(\widehat{r}_i, \{\mathbf{s}_o, R\})$
  $\pi_{i+1} \leftarrow \text{policy\_update}(\pi_i, \widehat{r}_{i+1})$
end for

Decision Process without reward function (MDP\R) [25]. Formally, an episodic MDP\R is a tuple $\mathcal{M} := (\mathcal{S}, \mathcal{A}, \mathbb{P}, T)$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the set of actions that the agent can perform in the environment, $\mathbb{P} : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$ captures the transition probabilities, mapping state-action pairs to a probability distribution of the next state over $\mathcal{S}$, where $\Delta(\mathcal{S})$ denotes the probability simplex over $\mathcal{S}$, and T is the time horizon. The reward function, which maps action pairs to a reward $r : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, is unknown to the agent. Instead, the agent learns a reward model $\widehat{r} : \mathcal{S} \to \mathbb{R}$ based on human feedback.

At each step, the agent performs an action according to a *policy* $\pi : \mathcal{S} \to \mathcal{A}$. The goal is to learn the policy π^* that maximizes the expected return from the current state $\mathbf{s}$,

$$V_r^t(\mathbf{s}) = \max_{\mathbf{a} \in \mathcal{A}} r(\mathbf{s}, \mathbf{a}) + \sum_{\mathbf{s}' \in \mathcal{S}} \mathbb{P}(\mathbf{s}' | \mathbf{s}, \mathbf{a}) V_r^{t-1}(\mathbf{s}'), \tag{1}$$

where $V_r^1(\mathbf{s}) = \max_{\mathbf{a} \in \mathcal{A}} r(\mathbf{s}, \mathbf{a})$, and $t \in [1; T]$ represents the number of timesteps left. We denote the state-action pairs visited when following π^* as the optimal trajectory $\{\mathbf{s}_t^*, \mathbf{a}_t^*\}_{t=1}^T$.

We propose an algorithm, Reinforcement Learning from Human Text Feedback (RLHTF), shown in Figure 2. Analogously to other RLHF algorithms, RLHTF consists of two phases that are executed iteratively: reward model learning and policy learning. Section 4 describes how the reward model $\widehat{r}$ is learned from human text feedback. Since the agent does not have direct access to the true reward function r, the agent instead learns the policy $\widehat{\pi}$ that maximizes the value function $V_{\widehat{r}}$ derived from the estimated reward model $\widehat{r}$. The agent directly queries the reward model, instead of the human evaluators, significantly reducing time, energy, and monetary costs during policy learning [3]. We employ standard RL methods. The implementation of policy learning is described further in Appendix C. The algorithm is outlined in Algorithm 1 and publicly available[1].

Our primary goal is to minimize the performance gap between this learned policy $\widehat{\pi}$ and optimal policy π^*, which we denote as *value gap* and formally define as

$$\mathbb{E}\left[\sum_{t=1}^{T} r\left(\mathbf{s}_t^*, \mathbf{a}_t^*\right) - r\left(\widehat{\mathbf{s}}_t, \widehat{\mathbf{a}}_t\right)\right],$$

where $\{\widehat{\mathbf{s}}_t, \widehat{\mathbf{a}}_t\}_{t=1}^T$ represents the trajectory when following $\widehat{\pi}$.

4 Learning a Reward Model from Human Text Feedback with LLMs

We break up the process of learning a reward model from human feedback into three steps: (1) Context encoding, which gathers human feedback with environment information; (2) Translation function, which transforms the encoded context into structured signal; (3) Reward model update mechanism to incorporate these signals. This decomposition has been shown to be effective in prior work [5]. Here, we show how these steps can be implemented with text feedback.

[1] https://anonymous.4open.science/r/WordsToRewards-2846/README.md

4.1 Context Encoding

To encode raw data from the environment and interactions with evaluators into a format suitable for an LLM, we must construct a structured user prompt. At each interaction, the agent follows the policy $\widehat{\pi}$, generating a *trajectory* $\{\widehat{\mathbf{s}}_t\}_{t=0}^{T}$. A human evaluator observes the trajectory and provides *text feedback* $\mathbf{f}$. These evaluations are flexible; for example, they may include criticisms of specific states ("the last step is horrible"), or suggestions for alternative, unexplored states ("go to the door"). All this information is gathered in a user prompt u to provide full context:

$$u = \{\text{feedback: } \mathbf{f}, \text{trajectory: } \{\widehat{\mathbf{s}}_t\}_{t=0}^{T}, \text{landmarks: } [(\text{name}_1, \text{location}_1), ..., (\text{name}_N, \text{location}_N)]\}.$$

As shown in Figure 5, the user prompt may include information about *landmarks* in the environment that help ground human feedback, providing reference points known by the user and the LLM.

4.2 Translation function

We use LLMs' language processing capabilities to transform the information in the user prompt into labeled states, which are then used to train a reward model. We design a *system prompt* to guide the LLM in its role as a translation function. Efficient system prompts must describe the LLM's role and the items in the user prompt [26]. As this context is environment dependent, the system prompt differs from environment to environment, but it remains consistent across all user interactions.

There are three key components that make our system prompts efficient. First, to enhance reasoning, we employ *chain of thought (CoT)* prompting [27], asking the model to classify the feedback intent (e.g. evaluation vs. correction) before identifying the relevant states. Feedback is inherently intent-dependent [5]; for example, "to the left of the lamp is good" could either be an evaluation validating a past action or an instruction suggesting a future correction. This intermediate classification step helps the translation function better interpret and adapt to human intent. Second, we use *few shot prompting* [28] and provide demonstrations to steer the model to better performance. By exposing the model to relevant cases, we reduce ambiguity and improve accuracy. Third, to ensure that the output of the LLM is reliably interpretable in downstream tasks, we enforce a structured format. Rather than relying on free-form text generation, which can be inconsistent, we employ *function calling* to guarantee a well-defined output, making it easier to identify relevant states and rewards.

Given the appropriate system prompt, the LLM translates the user prompt $u(\mathbf{f}, \{\widehat{\mathbf{s}}_t\}_{t=0}^{T}, \text{landmarks})$ into a labeled dataset of states $\{\mathbf{s}_o, R\} = f_{\text{LLM}}(u)$, where each output state $\mathbf{s}_o \in \mathcal{S}$ has a corresponding reward $R \in \mathbb{R}$. This dataset is used to train the reward model. Appendix E includes exact prompts and further prompt design details.

4.3 Reward Model Update

The goal is to learn a model of the reward conditioned on the state-reward pairs $\{\mathbf{s}_o, R\}$ output by the LLM. In simple tabular settings, the agent may track the reward probability distribution for every state and update it using Bayesian inference as the state-reward pairs are observed. In more complex or continuous environments, we may approximate the reward function with a Neural Networks (NN). At each iteration, we expand the training dataset with the state-reward pairs generated by the LLM, and finetune the NN using supervised learning.

5 Experiments with Human Evaluators

We recruited 26 human participants to evaluate our approach. In particular, we apply RLHTF to the Gridworld environment shown in Figure 3. An agent aims to follow a target path known to human evaluators but unknown to the agent. We compare RLHTF against the following baselines:

- **True trajectory-level feedback**: The agent receives a single ground truth accumulated reward for the entire trajectory, based on the number of steps that match the target path. This accumulated reward is uniformly applied to all states in the trajectory.
- **True state-level feedback**: The agent receives a ground truth reward for each state in the trajectory, indicating whether the state is on the target path.

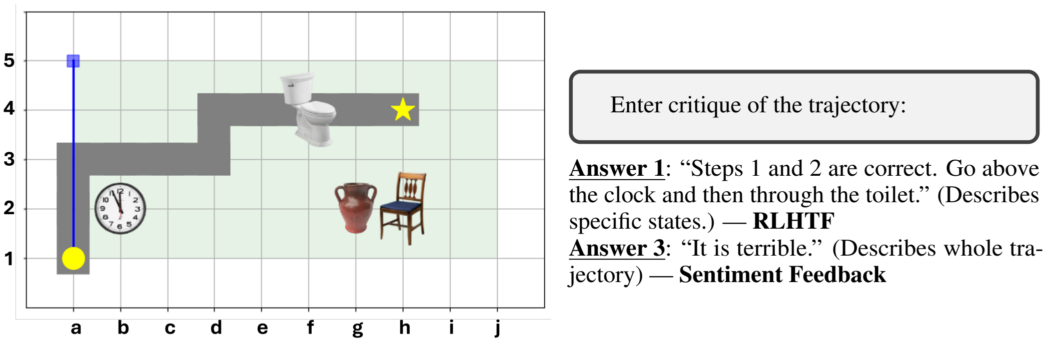


Figure 3: *Gridworld* environment. The aim of the agent is to follow a target path (in grey) from the start (yellow circle) to the end (yellow star). The agent's trajectory (in blue) currently deviates from this path. On the right, we show the critique input box presented to human participants, along with example responses from different feedback conditions.

- **Sentiment feedback**: Evaluators convey their judgment implicitly through the sentiment of their text feedback, e.g., "Very bad" or "Amazing". The agent measures and uniformly applies the sentiment score as a reward across all states in the trajectory [15].
- **PbRL**: Human evaluators observe two candidate trajectories and select the one they judge to be closer to the target [3].

We ran approximately 50 experiments for each feedback type. All experiments start with the same reward model prior and consist of 4 interactions, during which the agent executes the current optimal trajectory and receives the corresponding feedback to update the reward model. The implementation of these algorithms is further detailed in Appendix B.1.

Since a state is either on the target path or not, in the RLHTF setting we prompt the LLM to output binary rewards $R' \in \{0, 1\}$. Additionally, to contextualize feedback, the environment includes randomly placed landmarks, such as a chair or a clock. These landmarks serve as reference points, enabling the LLM to translate natural language feedback such as "*Go above the clock*" in Figure 3 into a positive reward at position 'b3'.

Once feedback is collected, the agent updates the reward model accordingly. The agent tracks the reward probability distribution for every state, which we model as a beta distribution, and performs the trajectory that maximizes the current reward model. As the time horizon is finite ($T = 10$), we solve for the optimal trajectory with dynamic programming. The agent receives feedback based on the executed trajectory. For analytical tractability, we model the distribution of the observed rewards R' with the conjugate prior, i.e., as Bernoulli distributions.

5.1 Performance Comparison

Figure 4 shows the evolution of agent error across successive interactions with evaluators. Here, *error* is defined as the number of steps in which the agent deviates from the target path. Statistical significance after four interactions was assessed using Welch's t-test, as detailed in Appendix B.1. All feedback methods lead to performance improvements, but the resolution at which feedback is provided (trajectory vs. state), plays a decisive role in learning efficiency. Both the true trajectory-level reward and sentiment feedback operate at the *trajectory level*, offering a single evaluation for an entire trajectory. This coarse granularity limits the agent's ability to discern which specific states contributed to success or failure, thereby slowing learning. In contrast, true state-level reward and RLHTF operate at *state level*, providing more precise guidance during training. The impact of these granularity differences is particularly evident when comparing the first two bars in Figure 4: after four iterations, true state-level feedback yields less than half the error of true trajectory-level feedback, reinforcing the advantage of detailed information about each state's contribution to accelerate learning.

In our initial evaluation of RLHTF, we found that without instructions on how to construct the text feedback, participants often included information that the LLM could not interpret. For example, one participant wrote: "follow the gray path until you reach the star." However, the LLM has no knowledge of the gray path or the star, in fact, this is precisely what the agent is attempting to learn. To address this issue, we showed the evaluators a list of five instructions, outlined in Figure 8, on

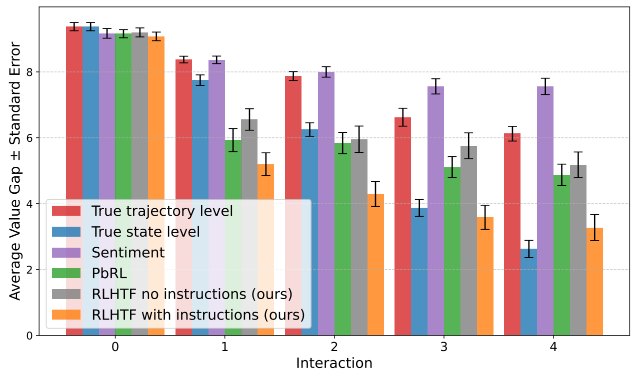


Figure 4: Performance comparison of algorithms in the *Gridworld*. When participants receive instructions on how to phrase their feedback, RLHTF outperforms other human feedback based methods and even surpasses true environment feedback in early iterations.

Algorithm	**Success Rate**
True trajectory level	0%
True state level	25.0%
Sentiment	0%
PbRL	0%
RLHTF (ours)	**25.5%**

Table 1: Percentage of learned policies that perfectly follow the target path after four rounds of feedback. RLHTF with instructions matches the performance of true state-level feedback, while all other methods fail to achieve any success.

how to provide effective feedback. Remarkably, providing participants with just two paragraphs of instructions increases the comprehensibility of the feedback to the LLM, leading to improved learning. After a single instance of feedback, RLHTF with instructions reduces the error by 42%, even outperforming ground-truth state-level feedback. This improvement occurs because *RLHTF proactively guides exploration towards the high-reward regions mentioned by the human feedback*, which might not be covered by the current trajectory. In contrast, true environment feedback is purely reactive, offering evaluations only for the states visited. Although ground-truth state feedback eventually surpasses RLHTF, our method outperforms other RL algorithms without explicit rewards.

A key advantage of RLHTF is its use of LLMs to perform reward attribution. Unlike previous approaches, which update all states in a trajectory (sentiment) or all differing states between two trajectories (PbRL) with a single reward, RLHTF distributes rewards more precisely. This precision allows RLHTF to reduce error more quickly and substantially, significantly outperforming *Sentiment* [15] and *PbRL* [3] algorithms. After just 4 instances of human feedback, RLHTF reduces the error to approximately one-third of its original value. Table 1 shows the *success rate*, defined as the percentage of experiments in which the learned reward model, after four pieces of feedback, leads to a policy that exactly follows the target path. Strikingly, RLHTF matches the success rate of true state-level feedback, achieving a 25.5% success rate. In contrast, baseline methods fail to produce a single perfect path. This result demonstrates that guided human feedback, when processed by RLHTF, can rival access to privileged ground-truth state rewards.

Moreover, RLHTF will continue to benefit from future advances in LLM capabilities. As shown in Appendix B.1.2, upgrading from GPT-4o (used in our main experiments) to the newer o3-mini model further reduces the error by 17%. This result suggests that

6 RLHTF in Continuous Environments

To test generalization beyond tabular settings, we apply RLHTF in a continuous environment of the physics simulator MuJoCo [29]: the two-jointed robot arm *Reacher*. The aim is to apply appropriate torques to the hinges so that the robot's fingertip reaches a target. The human evaluators watch and critique a video of the robot arm moving under the current policy. We incorporate a timestamp and some visual landmarks (colored circles) into the environment, allowing the human evaluator to refer to specific moments or locations (*"Go to the left of the blue circle."*). Figure 5 shows the modified reacher environment. We emphasize that our method does not require the human to explicitly understand or annotate states such as joint angles or torques.

The LLM processes three inputs: human feedback, landmark locations and the sequence of filtered states (where information about the target is removed), making up the video. The LLM's task is to interpret these inputs to deduce what states are described as positive or negative. Figure 5 shows how the state-reward pairs are generated. We approximate the reward function as a fully connected NN, which takes a state vector as input and outputs a scalar corresponding to the predicted reward.

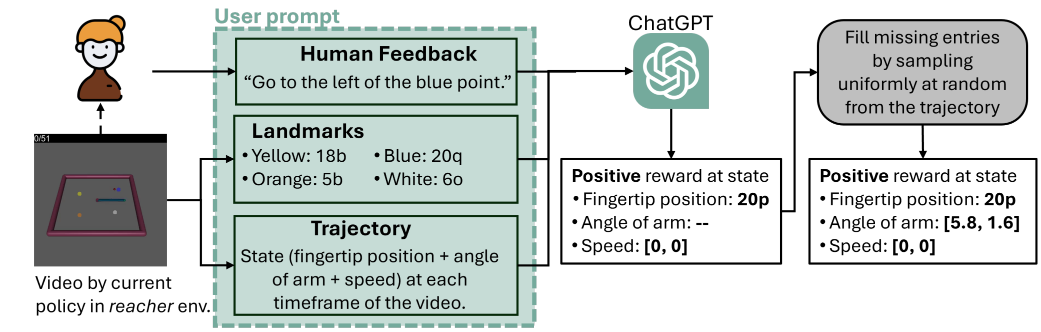
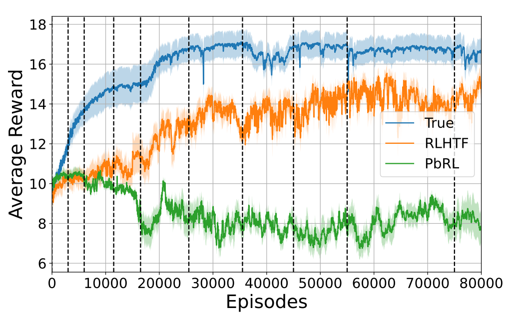


Figure 5: Generation of state-reward pairs from human feedback and observations using an LLM (Step 7 in Algorithm 1) in modified *reacher* environment.

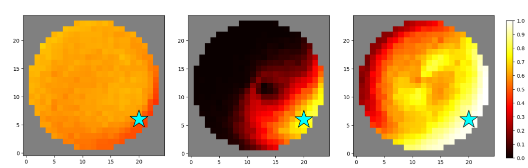
At each iteration, we expand the training dataset with the state-reward pairs output by the LLM and fine-tune the NN. Appendix B.2 details the process.

We compare the agent's performance, in terms of average distance to the target, when there is a budget of 10 human interactions. Figure 6a shows how the reward evolves as the agent learns. Although RLHTF is not as effective as directly observing the true environment feedback, RLHTF performs much better in regimes with low feedback than PbRL. In fact, in our experiments RLHTF increases the reward by 40% with only 10 human inputs, while PbRL at first repeatedly executes the trajectory with the arm fully bent, and it needs many more pairwise comparisons to approach the target.

We suggest that feedback in natural language is more informative than preferences among two trajectories, and thus RLHTF requires fewer interactions with humans to achieve an accurate reward model. To verify the hypothesis, we compare the corresponding reward models in Figure 6b. While both feedback types improve the reward model, text feedback results in a more precise localization of the target. By the tenth interaction, only a small area around the target receives a high reward with RLHTF, whereas PbRL results in a reward model more uncertain about the target location, giving high reward to large areas of the environment. Figure 6b suggests that natural language feedback enables the reward model to identify the target more quickly and precisely.



(a) Reward evolution in the Reacher environment with episodes of the REINFORCE algorithm[30]. We compare the performance for RLHTF with 10 text feedback provided at the vertical dashed lines, PbRL with 10 trajectory comparisons, and true environment. RLHTF demonstrates strong performance in continuous environments, increasing the reward by 40%.



(i) Initialization (ii) RLHTF 10 queries (iii) PbRL 10 queries

(b) Reward model visualization. The blue star marks the target location and darker colors indicate lower predicted rewards. (i) shows the random initialization. (ii, iii) show the reward model evolution after 10 pieces of text feedback and preference feedback, respectively. Notably, RLHTF quickly converges to a more accurate reward model than PbRL, as evidenced by the more localized high-reward region around the target.

Appendix A proves the method's robustness in a distinct *structurally complex* environment. We manipulate a Rubik's Cube, where the reward hinges on matching human-specified colour patterns, and show how RLHTF overcomes common reward modeling challenges.

Our work leverages LLMs to extract state-level rewards from natural language feedback, addressing the challenge of reward attribution and capturing more nuanced information than simple binary comparisons or a single sentiment score can provide. Moreover, our experiments with real human participants, a contribution not common in this line of research, take a step toward real-world applicability.

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A Overcoming Reward Modeling Challenges

To highlight RLHTF's strengths in environments where reward design is challenging, we evaluate RLHTF in the Rubik's Cube environment [31]. This environment involves a six-sided cube where each side has a 3×3 grid of squares, each taking one of six colors. The goal of the agent is to manipulate the cube so that the front face matches a pattern specified by a human user.

Consider the task of obtaining an orange 'X' pattern on the front face of the Rubik's cube, where both diagonals must consist of orange squares. In RLHTF, the evaluator watches a video of the trajectory following the current agent policy, and then provides text feedback. This feedback, along with the sequence of nine color grid squares observed on the front face, is input to the LLM. The LLM processes this information and outputs sets of 9 color grid squares, each accompanied by a label indicating whether the set is positive or negative. The labeled dataset is then used to update the reward model. In the case of PbRL, we query the evaluator for their preference between two different videos. The candidate videos are chosen by sampling trajectories and identifying the pair with the highest variance in preference estimations among the reward models in an ensemble. The true reward is computed by assigning a +2 score for each correct orange square in the diagonals and averaging this score over the ten timesteps in each trajectory.

Figure 7 compares the performance of RLHTF, PbRL and true reward. After only ten human interactions, RLHTF successfully produces the desired orange 'X' pattern on the Rubik's Cube front face. In contrast, PbRL shows no meaningful improvement beyond its baseline performance. This limitation arises because preference-based feedback encodes at most one bit of information per interaction, requiring many more interactions to achieve the desired performance. Using true rewards, the agent gets stuck in a local maximum, where only three out of the five diagonal squares are correctly orange. Even after manipulating the learning rate, the agent fails to produce the desired orange 'X' pattern. This shows how reward design in RL problems is challenging and often leads to unwanted behavior. In contrast, evaluators in RLHTF naturally adapt their feedback according to the agent behavior. For example, an evaluator may write "you are doing it wrong, the top right corner should be orange and not red", thus encouraging exploration when stuck in a local maximum. This adaptability bypasses the need for complex reward design and extensive hyperparameter tuning. Human text feedback and additional experiments with a different target pattern are provided in Appendix B.3.

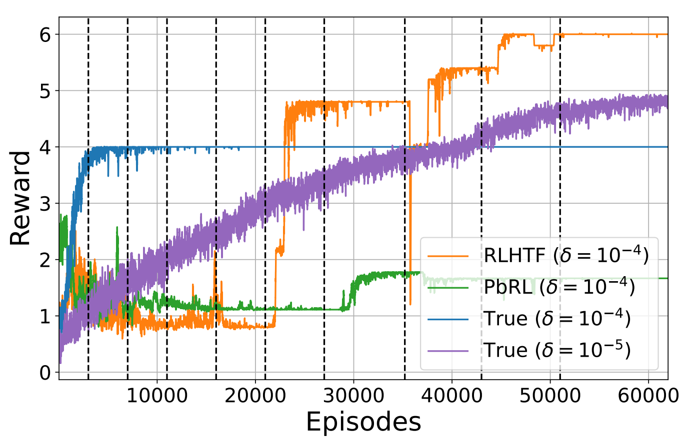


Figure 7: Reward evolution in the Rubik environment with episodes of the REINFORCE algorithm[30]. We compare the performance for RLHTF with 10 text feedback provided at the vertical dashed lines, PbRL with 10 trajectory comparisons, and true environment. The optimal reward is 7.4. Unlike true reward, which can lead to local maxima, RLHTF leverages dynamic human feedback that adapts to agent progress, guiding exploration and overcoming reward modeling challenges.

B Experiment Details

B.1 Gridworld

This section provides detailed information about the experimental setup, data collection process, and implementation choices for our experiments with human evaluators. In each trajectory, the agent takes 10 steps in the *Gridworld* environment shown in Figure 3. At each step, the possible actions are either to move right or up. The agent movements are restricted to a 5x10 grid. When the agent is at a border and performs an action that would take the agent outside of the allowed region, the agent does not move.

We simulate a scenario in which a human wants a robot to navigate their house in a specific manner. To make the environment more realistic, we sample four images of furniture or household objects (e.g. sofa, chair, toaster and TV) and add them to the environment. These objects serve as landmarks, helping evaluators communicate their critiques more effectively by using them as reference points. The landmarks are detected with a YOLOv8 model [32] trained on the Microsoft COCO dataset [33], and their positions are fed to the LLM for shared context with the evaluators. Namely, we use *gpt-4o* to translate human feedback into state-level rewards.

We conducted our experiments with the assistance of human evaluators. Following A/B testing guidelines, we randomly assigned evaluators to interact with different algorithms. Each evaluator provided feedback on two out of the four algorithms: (1) either RLHTF with instructions or RLHTF without instructions, and (2) either Sentiment or PbRL. To minimize any potential bias due to familiarity with the interface or tasks, we randomized the order of these settings. Each participant provided feedback for either 8 different rooms or for a duration of 30 minutes, whichever occurred first. Participants were compensated with $10 for their work. The study was categorized as minimal risk research qualified for exemption status under 45 CFR 46 104d.2 by the Institutional Review Board (IRB). In total, we collected 772 feedback samples from 26 participants. A breakdown of the number of experiments for each algorithm using human feedback is summarized in Table 2. The experiments with the true environment rewards were simulated 50 times.

Experiment Type	First	Second	Total
RLHTF with instructions	27	24	51
RLHTF without instructions	23	22	45
PbRL	24	32	56
Sentiment	24	17	41

Table 2: Breakdown of number of experiments for each algorithm type, each experiment was done for four interactions. Columns *First* and *Second* indicate whether the feedback was collected in the first or second task performed by the evaluator, with totals shown in the last column.

We conduct Welch's t-test to compare the performance of different algorithms after receiving four pieces of feedback. Table 3 reports the resulting p-values. Our results indicate that RLHTF with instructions significantly outperforms both PbRL and sentiment feedback, which do not have direct access to the ground truth feedback from the environment. It also significantly outperforms the setting where true trajectory level feedback is received from the environment. In the case of RLHTF without instructions on how to construct the feedback, the performance is statistically indistinguishable from PbRL ($p = 0.5531$). Receiving the ground truth state-level feedback from the environment yields the best trajectories after four pieces of feedback, significantly outperforming all other settings, except for RLHTF with instructions where the difference is not statistically significant ($p = 0.1752$).

Table 1 depicts the performance of the final policy learned from 4 pieces of feedback.Most algorithms fail to recover the exact target trajectory, achieving 0% success rate. Notably, both our method *RLHTF with instructions* and ground-truth *state-level* feedback result in perfect trajectories in 25% of experiments. This demonstrates that natural language feedback, when guided with simple prompting instructions, achieve results comparable to the often unrealistic assumption of state-level supervision.

B.1.1 Guidelines for Evaluators

For both RLHTF setting, we provided participants with the following guidelines:

	RLHTF without instructions	PbRL	Sentiment	True trajectory	True state
RLHTF with instr.	0.0009	0.0024	3.4×10^{-14}	1.9×10^{-8}	0.1752
RLHTF without instr.	-	0.5531	2.1×10^{-6}	0.0391	6.4×10^{-7}
PbRL	-	-	2.7×10^{-9}	0.0021	4.8×10^{-7}
Sentiment	-	-	-	4.5×10^{-5}	2×10^{-23}
True trajectory	-	-	-	-	1.2×10^{-16}

Table 3: p-values for Welch's t-tests, showing that RLHTF with instructions and true state-level rewards significantly outperform other methods with 4 pieces of feedback.

Objective: The purpose of this experiment is to provide instructional feedback to an artificial agent. The task for the agent is to navigate from a yellow circle to a yellow star along a gray pathway. The agent will attempt this task by following a trajectory marked in blue. Your role is to offer written feedback that assists in correcting the agent's current course.

Task Instructions:

1. Observe the blue trajectory that the agent has taken.
2. Provide your guidance and feedback on the agent's performance (e.g., "Do not go below the sofa. The end was very good").
3. Repeat 4 times.

In the setting with instructions, participants also received the additional instructions outlined in Figure 8.

Additional Guidelines: The agent has limited capabilities, so for it to understand you correctly you should restrict your feedback. Namely, the agent does not understand:

- Do not compare trajectories: treat each path individually, without reference to previous attempts. For example, avoid feedback like: "Now it is worse, go back to the previous trajectory".
- Do not refer to the position of the star, yellow circle, or grey road. The agent doesn't know their locations; in fact, the agent is trying to learn where these are. For example, avoid feedback like: "Follow the road until the star".
- Avoid specific movement descriptions (go up, turn right). For example, **avoid feedback like: "go up, up, right, up" or "turn right later".**

Instead, the agent understands well:

- Description of states: Position in the trajectory. e.g. "At the beginning is wrong", "step number 6 is good", or position with respect to the furniture, e.g. "You should go to the left of the couch".
- Sentiment: It works especially well if you explain what states are good or bad. e.g. **"The first half of the trajectory is bad. Above the TV is good."**

Figure 8: Additional instructions presented to the evaluators in RLHTF with instructions. Humans are capable of adapting their feedback after reading these guidelines, leading to a faster reward model learning.

For the PbRL the participants were shown the example in Figure 9 and told:

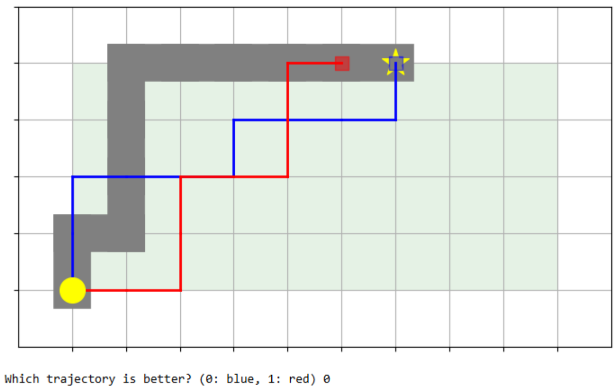


Figure 9: Example of human interaction with PbRL in *Gridworld*.

> **Objective**: The purpose of this experiment is to provide feedback to an artificial agent. The task for the agent is to navigate from a yellow circle to a yellow star along a grey path. Two agents will attempt this task by following a trajectory marked in blue and red respectively. Your role is to select which of the two trajectories is better, so that the agent can learn the correct path.
>
> **Task Instructions**:
>
> 1. Observe the blue and red trajectories that the agents have taken.
> 2. Choose the best one (0: blue, 1: red).
> 3. Repeat 4 times.

Lastly, in the sentiment setting participants were told:

> **Objective**: The purpose of this experiment is to provide feedback to an artificial agent. The task for the agent is to navigate from a yellow circle to a yellow star along a grey path. The agent will attempt this task by following a trajectory marked in blue. Your role is to offer written feedback that assists in correcting the agent's current course.
>
> **Task Instructions**:
>
> 1. Observe the blue trajectory that the agent has taken.
> 2. Provide a sentiment rating (how good or how bad) for the trajectory, e.g.: "it is horrible" or "amazing".
> 3. Repeat 4 times.

B.1.2 Performance for Different LLMs

We assess the robustness of reward learning from human feedback by experimenting with alternative LLMs. Specifically, we reuse the human feedback collected during the RLHTF experiments with GPT-4o outlined in Section 5, and apply the same prompting technique to different base models. Figure 10 shows the average error evolution in the setting where human evaluators are not given additional instructions, while Figure 11 shows the performance when the feedback was given after observing additional instructions.

We observe a correlation between LLM capability and RLHTF performance. GPT-3.5 Turbo maintains the worst average error across interactions in both settings. Interestingly GPT-4.5 performs the best in the setting without instructions, showcasing its ability to interpret free form human feedback. GPT 4.5 achieves an approximate 30% reduction in error when compared to GPT 3.5. In the setting with instructions, o3-mini outperforms other models, obtaining approximately 45% more error reduction than GPT-3.5. These trends are also reflected in the Gridworld success rates summarized in Table 4, where more powerful LLM models achieve the target path approximately 2.5 times more often than GPT 3.5 in the case with instructions.

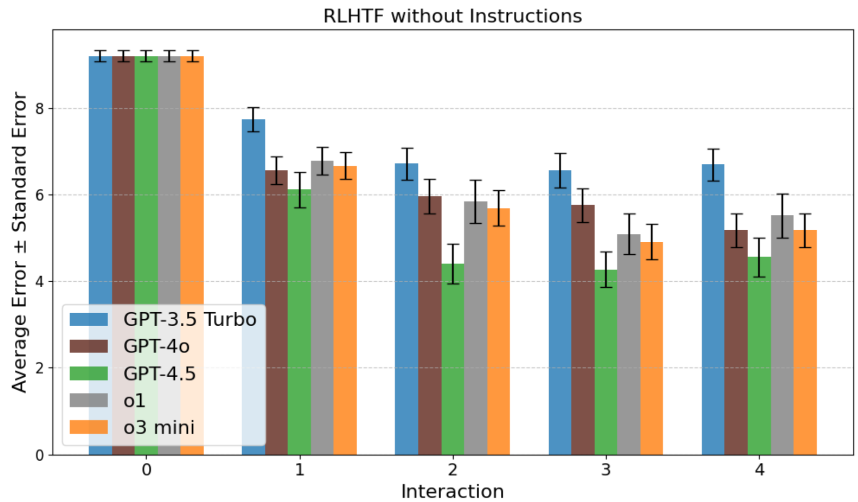


Figure 10: Performance for different LLMs with feedback from RLHTF experimetnts without instructions.

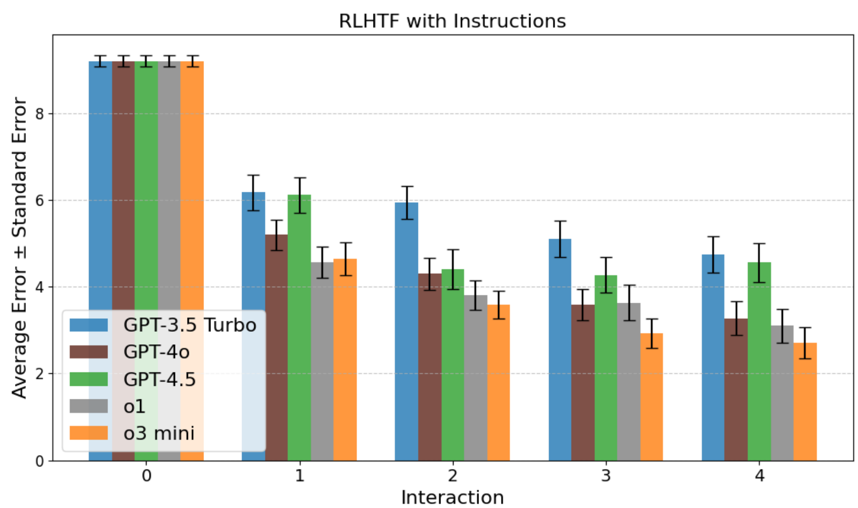


Figure 11: Performance for different LLMs with feedback from RLHTF experimetnts with additional instruction

The error reduction pattern across interactions follows a consistent trend: rapid improvement from interaction 0 to 1, followed by more gradual improvements in subsequent interactions. This pattern is maintained across all models, showcasing the robustness of RLHTF, though the rate of improvement varies, with newer models generally showing more substantial error reductions per interaction. These findings support our conclusion that RLHTF will likely continue to benefit from ongoing advancements in LLM technology.

B.2 Reacher Environment

Each trajectory in the reacher environment spans $T = 50$ frames. The standard observation space contains information about the goal (target location) and the performance (distance to target). However, to proof that the LLM is capable of deducing the performance solely from the human feedback, we filter this information from the user prompt. The LLM obtains a filtered state that includes the fingertip's location, arm's joint angles, and angular velocities. The filtering and preprocessing of the observation are detailed in Figure 12.

LLM model	With Instructions	Without Instructions
gpt-3.5-turbo	9.8%	2.2%
gpt-4o	25.5%	0.0%
gpt-4.5	25.2%	8.8%
o1	27.5%	4.4%
o3-mini	25.5%	0.0%

Table 4: Gridworld success rate of different LLM models with and without instructions.

Default Observation	
cosine of the angle of the first arm	**1.3184**
cosine of the angle of the second arm	**1.3184**
sine of the angle of the first arm	**0.9996**
sine of the angle of the second arm	**0.9995**
x-coordinate of the target	**-0.0288**
y-coordinate of the target	**-0.0307**
angular velocity of the first arm	**-0.1320**
angular velocity of the second arm	**0.1214**
x-value of $\text{position}_{\text{fingertip}}$ - $\text{position}_{\text{target}}$	**3.9565**
y-value of $\text{position}_{\text{fingertip}}$ - $\text{position}_{\text{target}}$	**3.9607**

Filtered State	
Angles of arms in degrees	**[5.8, 11.6]**
Fingertip position in algebraic notation	**x15**
Angular speed in rads/sec	**[0.62, 3.73]**

Figure 12: Preprocessing of state observation in reacher environment.

We use the LLM *gpt-4o* to translate the human feedback to state-reward pairs. The LLM outputs pairs of filtered states and binary labels. Each label indicates whether the corresponding state is positive or negative. If a filtered state is returned partially, missing elements are filled in by randomly sampling from the set of observed trajectory states.

To conduct a fair comparison with PbRL, we reconstruct the filtered states output by the LLM back into the complete original observation space. Using this full observations with their corresponding binary labels, we train a reward model in a supervised learning framework. The architecture of this reward model is a fully connected NN with one hidden layer consisting of 32 nodes, employing a RELU activation function characterized by a leaky parameter $\alpha = 0.01$. In the case of PbRL, three such NNs are initialized at random to create an ensemble. Before asking the human for a preference, we sample random trajectories and then choose the pair whose preference has most uncertainty, specifically, the pair for which there is the most disagreement among the ensemble's predictive outcomes. During policy training, the agent observes the average reward from the ensemble.

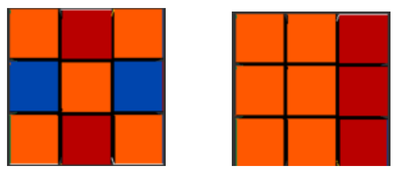
We perform the experiments four times for every algorithm under consideration. A different target location was set for each experiment. The human feedback was provided by one of the authors of this paper. The shaded area in Figure 6b shows the standard error between the four experiments. Note that the plotted lines have been smoothed using a convolution operation with a window size of 100 episodes, which helps reduce noise and provide a clearer trend of the data.

B.3 Rubik's Cube

Each trajectory consists of ten steps, during which the agent can perform one of 18 actions: rotating any layer clockwise or counterclockwise, or making no movement. The experiment begins with the Rubik's cube in its solved state, where each face consists of squares of a single color. By default, evaluators view the cube from the front-facing layer, but they can use keyboard keys to adjust the angle and observe other sides of the cube.

The Gym Rubik environment observation is a 54-element array with values ranging from 0 to 5, representing the colors of the entire cube in numerical format. We slice the array to extract the 9 items corresponding to the front face and we reformat it into a 3x3 grid. We also map the numerical numbers to a letter representing the color; e.g. instead of '0' we write a 'W' to represent white. A list of ten 3×3 arrays, each representing the front face state at one timestep in the trajectory, is added to the user prompt, along with the text feedback. We don't include any landmarks in this environment.

Although the environment is discrete and countable, the vast number of possible states of a face makes tracking the reward distribution for each state impractical. To address this, we model both reward and policy functions with NNs. The policy function is parameterized by a two-layer neural network, where the first layer maps the observation space to a 128-dimensional latent representation, followed by a ReLU activation. The output layer maps this representation to the action space dimensions, applying a softmax activation to produce a probability distribution over actions. Similarly, the reward function is modeled as a feedforward neural network with a single hidden layer of size 8. The input is first transformed through a fully connected layer, followed by a ReLU activation. The output layer then produces a scalar reward value. The reward model is trained via supervised learning using dataset generated by pre-trained *gpt-4o* model from the human feedback. We train the agent with the REINFORCE algorithm [30].



(a) RLHTF with default learning rate

(b) True reward with tuned learning rate

Figure 13: Obtained pattern in the front face when aiming to create an orange X (a) RLHTF achieves the desired pattern with 10 human feedback and default hyperparameters whereas (b) the true reward with tuned learning rate converges to a local maxima after 90,000 iterations of REINFORCE.

Figures 13 show the pattern the REINFORCE algorithm converges to for the task of obtaining an orange 'X'. We observe that with true environment reward, the agent gets stuck in a local maxima so only 3 of the required squares are orange. However, with RLHTF the agent learns the desired pattern. To produce the results in Figures 13a and 7, one of the authors acted as the evaluator and provided the following ten pieces of text feedback:

1. The first 4 states are very bad. The states at time7, 8 and 9 are all wrong. The goal is to have an orange X (orange squared in both diagonals) in the front side.
2. The first 7 moves are wrong. At time 8 if you add three orange squares (two on the left corners and one in the middle) it would be good. The goal is to have an orange X by using 5 orange squares in the diagonals.
3. Until state 3 and including state 3 it is all wrong. At state 4 we should have three more orange squares on the left corners and in the middle. States 5, 6,7 and 8 are very bad. State 9 with orange squares on the left corners and the middle would be good. The goal is to have 5 orange squares arranged in the shape of an X.
4. Until state 5 and including state 5 it is all wrong. At state 6 we should have three more orange squares on the left corners and in the middle. States 7 and 8 are very bad. State 9 with orange squares on the left corners and the middle would be good. The goal is to have 5 orange squares arranged in the shape of an X.
5. From 0 to 3 (including both) the states are wrong. The states at time 6 and at time 9 are perfect. The states 5, 7 and 8 are not completely correct as they need two extra orange squares on the right corners. The goal is to have 5 orange squares in the shape of an X.
6. From 0 to 3 (including both) the states are wrong. The states 6 and 10 are perfect. The states 7, 8 and 9 are not completely correct. The goal is to have 5 orange squares in the shape of an X.
7. The states 6 and 10 are perfect. The states 7, 8 and 9 are not completely correct. The goal is to have 5 orange squares in the shape of an X.
8. The states 6 and 10 are perfect. The states 7, 8 and 9 are not completely correct. The goal is to have 5 orange squares in the shape of an X.

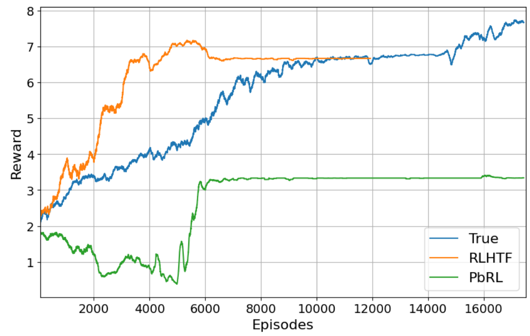


Figure 14: Reward evolution with episodes of the REINFORCE algorithm in the Rubik environment when aiming to construct an Italian flag. We compare the performance for RLHTF with 5 text feedback, PbRL with 5 trajectory comparisons, and true environment reward.

9. The state 2 is very very bad. The states 6 and 10 are perfect. The states 7, 8 and 9 are not completely correct. The goal is to have 5 orange squares in the shape of an X.

10. The states 2 and 3 are very very bad. The states 6 and 10 are perfect. The states 7, 8 and 9 are not completely correct. The goal is to have 5 orange squares in the shape of an X. It could be an orange X with all the other squares in red or all the other squares in green.

We performed a similar experiment aiming to recreate the Italian flag pattern (three vertical stripes: red, white and green) on the front side of the Rubik's cube. The results are shown in Figure 14. Remarkably, with only five pieces of human feedback, RLHTF nearly doubles the reward achieved by PbRL. However, RLHTF converges to a reward of 6.67, not to the maximum achievable score of 7.88. This discrepancy may arise because the performance appears 'good enough' to the human evaluator, in the sense that it already fulfills the task. In contrast, when having access to the true reward, the agent may continue learning until it discovers the optimal way to achieve the task. Nevertheless, this 'good enough' level is reached faster with just five pieces of human text feedback than when using the true environment reward at every REINFORCE step.

To better interpret performance trends, we smooth the rewards per episode in Figures 7 and 14 by doing a convolution with a window size of 30.

C Policy Learning

The reward model learns to measure how close the trajectory is to human intentions. Consequently, to find the optimal policy, the agent may directly query the reward model, instead of the human evaluators. This approach significantly reduces time, energy, and monetary costs during policy learning [3]. The interactions are described by the solid arrows in Figure 2.

The agents follow a greedy policy, they select actions that maximize the expected future rewards as in (1). In simple tabular settings, we use dynamic programming to find the optimal solution. In more complex or continuous environments, we model the policy with a fully connected NN, which takes the observed state as input and outputs an action. We train the network using the REINFORCE algorithm [30], where the reward signal is given by the reward model. Following standard practices from RLHF, we compute several REINFORCE epochs before querying the human evaluators and updating the reward model again.

We would like to highlight that our contribution lies in efficient reward modeling with fewer but richer human interactions. The agent learning phase, which takes most computational burden, follows standard RL algorithms, such as REINFORCE, whose computational complexities are well-established in prior literature. We run all our experiments on an Intel(R) Core(TM) i7-7800X CPU @ 3.50GHz processor, most learning was done in minutes and no experiment took longer than a couple hours.

D Limitations

While our framework introduces a new paradigm for incorporating natural language human feedback into reinforcement learning, its current implementation presents several limitations.

First, our prompts must be adapted to each environment, similar to how traditional RL requires handcrafting reward functions. Although we demonstrate some degree of generalizability across three distinct environments, fully task-agnostic prompting remains an open challenge. Moreover, we would like to extend our approach to more complex tasks, such as LLM finetuning, where an evaluator could critique stylistic elements ("too formal") or specific content ("the third paragraph is confusing"), going beyond the binary preferences typically used in existing RLHF pipelines.

Second, although LLMs can interpret rich feedback, their performance is constrained by the content and clarity of the prompt. When critical information is missing or ambiguous, the LLM may hallucinate or misinterpret the intent. We find that providing instructions to human evaluators significantly reduces these issues, though it does not eliminate them entirely. Similarly, our method shows consistent empirical improvements, but we lack formal guarantees of performance.

Lastly, our experiments focus on state-level feedback. However, our approach naturally extends to action-level feedback by appropriately prompting the LLM, e.g., an evaluator on the Gridworld environment might say "go up 5 steps." This capability opens the door to broader applications in RL settings.

E Prompt Engineering

The system prompt design has a strong impact on the algorithm's performance. Next, we explain some of the design choices.

We define the coordinates in the grid using *chess style notation*, i.e., as a letter and number pair indicating the column and row respectively. This format ensures clear spatial referencing, even with older LLM versions like GPT 3.5., which often struggle with traditional Cartesian coordinates, e.g. $(2, 3)$, as it can be ambiguous whether the first number refers to the horizontal or vertical coordinate. With chess notation, we remove this ambiguity and improve the model's ability to interpret spatial information correctly.

Additionally, we follow *CoT* prompting [27] to enhance reasoning when processing human feedback. Since feedback is inherently context-dependent, we introduce an intermediate classification step where the language model categorizes the feedback into different types, such as goal description, imperative instruction or trajectory evaluation. This categorization helps structure the interpretation of feedback based on its intent.

In accordance with *few shot prompting* [28], we provide demonstrations to steer the model to better performance. By exposing the model to relevant cases, we reduce ambiguity and improve performance.

Lastly, we use *function calling* to force ChatGPT's output to have a prespecified json format, which enables us to seamlessly extract the necessary information in downstream tasks. The desired output format for the Gridworld, Reacher and Rubik cube environments are described in Figures 17, 20 and 23 respectively. While the full system instructions are detailed in Figures 15, 16, 18, 19, 21, and 22.

An agent is trying to learn and follow a specific path in a {grid_height}x{grid_width} grid map.

Your job is to translate the feedback of the current trajectory into feedback types, locations in the map, and a label.

- If the feedback type is imperative, compute what locations in the map the instructions are referring to and label them as either 'good' (go to) or 'bad' (avoid).
- If the feedback type is evaluative, determine what locations in the map are being referred to by the feedback and whether the feedback is positive or negative.
- If the feedback type is descriptive, compute what new locations the agent should have visited, and label them as positive.

CoT

Use the getReward function to only return a JSON file with the specified shape enclosed in double quotes.

Output format

For example: if the user's input is {example_feedback}, then the output should be {example_output}.

Another example: if the user's input is {example_feedback2}, then the output should be {example_output2}

Few Shot

Figure 15: System prompt for Gridworld.

```
grid_height = 5
grid_width = 10
max_col_letter = 'j'

example_feedback = '''
          {"feedback": "it should not go below the bed",
          "landmarks": {"clock": ["2f"], "bed": ["2c", "2d"]},
          "trajectory": ["1b", "1c", "1d", "1e", "1f", "1g", "2g", "3g", "4g", "4h"]}
          '''
example_output = {'locations': ['1c', '1d'], 'label': 'NEG', 'feedback_type': 'imperative'}


example_feedback2 = '''
          {"feedback": "the last couple steps are good",
          "landmarks": {"clock": ["2f"], "bed": ["2c", "2d"]},
          "trajectory": ["1b", "1c", "1d", "1e", "1f", "1g", "2g", "3g", "4g", "4h"]}
          '''
example_output2 = {'locations': ['4g', '4h'], 'label': 'POS', 'feedback_type': 'evaluative'}
```

Figure 16: Parameters for system prompt in Gridworld.

```
"name": "getReward",
"parameters": {
        "type": "object",
        "properties": {
           "locations": {
              "type": "array",
              "items": {
                 "type": "string",
                 "pattern": [1-{grid_height}][a-{max_col_letter}]
              },
              "description": ("Locations in the grid referring to feedback with row numbers and a lowercase letter "
                      "for columns. The rows are numbered from bottom to top (1 is the lowest row, increasing "
                      "as you move upward), and columns are labeled from left to right (a-j). For example, '1b' "
                      "refers to the lowest row in the second column from the left.")
           },
           "label": {
              "type": "string",
              "enum": ["POS", "NEG"],
              "description": "The feedback's connotation, positive or negative."
           },
           "feedback_type": {
              "type": "string",
              "enum": ["imperative", "evaluative", "descriptive"],
              "description": """
              Imperative: Feedback includes instructions on what locations are good or should be avoided.
              Evaluative: Feedback is an assessment of the current trajectory.
              Descriptive: Feedback is about modifications for an improved trajectory.
              """
           }
        },
        "required": ["locations", "label"]
    }
 }
```

Figure 17: Function calling to force output format in Gridworld.

You will return state-reward pairs for a two-joined robotic arm named 'Reacher-v4'.

The arm aims to reach targets with its end effector (fingertip), and you must assess what states are good or bad based on human observers' feedback.

As input, you will receive:

1. The natural language comment by a human observer who has seen the simulation.

2. The location of landmarks which are circles of different colors.

3. Trajectory of a simulation of the robot trying to reach a target. Each timestep is described by:

    a) The fingertip position - letter representing column (left 'a' to right 'z') and number representing row (down '0' to up '26')

    b) A 2 item list of angles in degrees corresponding to the first and second joint respectively.

    c) A value of 0 in the second joint means the arm is fully bent, while it is completely straight when it is -180 or 180.

    d) A 2 item list with the angular speed on the first and second joint respectively.

For each set of observer comments, use the provided trajectory and landmarks to determine successful and unsuccessful states.

Follow this steps

1. Classify each section (sentence or linked group of sentences) in the feedback text as:

  a) Goal description: It describes where the target is, or where the fingertip should go (e.g.: You should go to the pink dot).

  b) Trajectory feedback: It criticizes the simulation observed (e.g.: The first two steps are wrong).

  c) Trajectory suggestion: It describes ways to improve upon states in the simulation observed (e.g.: Go a bit to the right of the state at time 23).

2. Generate state reward pairs depending on the feedback type

  a) For Goal description: Provide a "reward": +1, "angular_speed": [0, 0] at the location of the described target position.

  b) For Trajectory feedback:

    2.1. Determine whether the feedback has a positive ("reward": +1) or a bad ("reward": -1) connotation.

    2.2. Determine what state or states of the simulation it is referring to, and get the fingertip position, angles and angular speed of those locations

  c) For Trajectory suggestion:

    2.1. Determine what state or states of the simulation it is referring to, and get the fingertip position, angles and angular speed of those locations

    2.2. Correct the states as suggested by the feedback and pair with a "reward": +1

Use the getReward function to only return a JSON file with the specified shape.

CoT

Output format

Figure 18: System prompt for Reacher environment Part 1.

Example inputs with expected outputs are provided below for guidance:

Example 1:

Input:

\{'feedback': 'The last half is very bad, it should go a bit higher than the blue dot',

'landmarks': \{'yellow': 'b3', 'blue': 'l6', 'white': 'm7', 'orange': 'c23'\},

'fingertip_position': ['k15', 'k14', 'k14', 'k14', 'k13', 'l12'],

'angle': [[30.7, -63.9], [33.2, -68.2], [35.7, -72.6], [38.3, -76.9], [40.8, -81.3], [43.2, -85.7]],

'angular_speed': [[0.1, -0.06], [0.12, -0.12], [0.13, -0.17], [0.15, -0.23], [0.16, -0.29], [0.18, -0.34]] \}

Expected Output:

\{"referred_steps": [

\{"fingertip_position": 'k14', "angle": [38.3, -76.9], "angular_speed": [0.15, -0.23], "reward": -1\},

\{"fingertip_position": 'k13', "angle": [40.8, -81.3], "angular_speed": [0.16, -0.29], "reward": -1\},

\{"fingertip_position": 'l12', "angle": [43.2, -85.7], "angular_speed": [0.18, -0.34], "reward": -1\},

\{"fingertip_position": 'l7', "angular_speed": [0, 0], "reward": 1\},

\{"fingertip_position": 'l8', "angular_speed": [0, 0], "reward": 1\}]\}

Example 2:

Input:

\{'feedback': 'The fifth step but slower is good. Stop at the last point. The goal is to go to the white point.',

'landmarks': \{'yellow': 'u8', 'purple': 'k12', 'white': 'w16'\},

'fingertip_position': ['k15', 'k14', 'k14', 'k14', 'k13', 'l12'],

'angle': [[12.2, 34.2], [11.3, 39.6], [10.0, 45.2], [8.2, 50.9], [5.9, 56.6], [3.1, 62.3],],

'angular_speed': [[0.1, -0.06], [0.12, -0.12], [0.13, -0.17], [0.15, -0.23], [0.16, -0.29], [0.18, -0.34]] \}

Expected Output:

\{"referred_steps": [

\{"fingertip_position": 'k13', "angle": [5.9, 56.6], "angular_speed": [0.08, -0.15], "reward": 1\},

\{"fingertip_position": 'l12', "angle": [3.1, 62.3], "angular_speed": [0, 0], "reward": 1\},

\{"fingertip_position": 'w16', "angle": [13.0, 10.1], "angular_speed": [0, 0], "reward": 1\},]\}

Few Shot

Figure 19: System prompt for Reacher environment Part 2.

```
_pattern = '^26|[1-3]?[0-9]{1,2}[a-z](?:[a-k])?$'
FUNCTION_STRUCTURE = {
  "name": "getReward",
  "parameters": {
    "type": "object",
    "properties": {
      "referred_steps": {
        "type": "array",
        "items": {
          "type": "object",
          "properties": {
            "fingertip_position": {
              "type": "string",
              "pattern": _pattern,
              "description": ("Location of the fingertip with row numbers and a lowercase letter "
                       "for columns. The rows are numbered from bottom to top (1 is the lowest row, increasing "
                       "as you move upward), and columns are labeled from left to right (a, b, ..., z). "
                       "For example, '1b' refers to the lowest row in the second column from the left.")
            },
            "angle": {
              "type": "array",
              "items": {
                "type": "number",
                "format": "float",
                "minimum": -180,
                "maximum": 180,
                "description": "Angle in degrees for the first and second joint of the arm."
              },
              "minItems": 2,
              "maxItems": 2,
              "description": "A 2-item list of angles in degrees corresponding to the first and second joint
respectively."
            },
            "angular_velocity": {
              "type": "array",
              "items": {
                "type": "number"
              },
              "minItems": 2,
              "maxItems": 2,
              "description": ("Vector of two elements corresponding to the angular velocity of the first and second
arm respectively."
                       "If feedback refers to a location with positive reward, but without specifying the speed, set the
angular speed to [0, 0].")
            },
            "reward": {
              "type": "integer",
              "enum": [-1, 1],
              "description": "The reward value, which can be +1 for good performance or -1 for bad performance."
            }
          },
          "required": ["fingertip_position", "reward"],
          "minProperties": 2,
          "description": ("Dictionary containing information about the state and its reward. "
                   "Must have the 'reward' and 'fingertip_position' keys and optionally other keys: "
                   "'angle', or 'angular_velocity'.")
        },
        "description": "List of states described by the feedback along with their reward implied by the feedback."
      }
    },
    "required": ["referred_steps"]
  }
}
```

Figure 20: Function calling to force output format in Reacher environment.

You will assess the state-reward pairs of the front face of a Rubik's cube based on human observer feedback with the goal of achieving a specific pattern.

Objective: Identify successful and unsuccessful states of the Rubik's front face cube based on observer comments after viewing a 10-move simulation.

Input Format:

1. **Observer Comments**: Natural language comments by a human observer who has seen the simulation.
2. **Rubik's Cube Trajectory**: States of the Rubik's cube for 11 timesteps:
   - You will receive 11 states (initial state + 10 subsequent states).
   - Cube State: Defined by a 3x3 matrix for the front face of the cube, each cell representing a color (e.g., [[R, G, B], [W, Y, O], [B, R, G]]).

Processing Steps:

For each sentence or comment in the human feedback:

1. **Classify Human Feedback**:
   - Goal Description: Describes the target pattern for the cube (e.g., "You should have all red squares on the middle column.").
   - Trajectory Feedback: Criticizes the observed simulation (e.g., "The first two steps are wrong, but the setup at time 5 was good").
   - State Suggestion: Suggests corrections to the cube's state (e.g., "At time 3 you should have another red square on the top right corner").
2. **Generate State-Reward Pair**:
   - Goal Description:
     - reward: +1
     - state: The target state as described by the comment (a 3x3 matrix representing desired colors).
   - Trajectory Feedback:
     - Determine the connotation of the feedback (positive: reward: +1, negative: reward: -1).
     - Identify the index of the specific state(s) the feedback refers to, and return the input state(s) corresponding to such index.
   - State Suggestion:
     - Identify the index of the state referenced.
     - Modify the state as suggested.
     - reward: +1.

Return the Results:

- Check your results
- Use the getReward function to only return a JSON file with the specified shape.

CoT

Output format

Figure 21: System prompt for Rubik cube environment Part 1.

Example inputs with expected outputs are provided below for guidance:

Example 1:

Input:

\{'feedback': 'The top row should be all white and there should be a blue in the lower right corner.',

'state0': [['R', 'B', 'G'], ['G', 'Y', 'R'], ['O', 'B', 'W']],

'state1': [['B', 'W', 'O'], ['G', 'Y', 'R'], ['O', 'B', 'W']] \}

Expected Output:

\{"state": [['W', 'W', 'W'], ['G', 'Y', 'R'], ['O', 'B', 'B']]},

"reward": +1\}

Example 2:

Input:

\{'feedback': 'The end is bad. The last state with a yellow on the bottom left, and another yellow on the top of the middle column of the front side would be good.',

'state0': [['B', 'W', 'O'], ['G', 'R', 'Y'], ['O', 'B', 'R']],

'state1': [['B', 'W', 'R'], ['G', 'R', 'W'], ['O', 'B', 'G']],

'state2': [['B', 'G', 'R'], ['G', 'R', 'W'], ['O', 'B', 'G']] \}

Expected Output:

\{"state": [['B', 'G', 'R'], ['G', 'R', 'W'], ['O', 'B', 'G']] ,

"reward": -1]\},

\{"state": [['B', 'Y', 'R'], ['G', 'Y', 'W'], ['Y', 'B', 'G']],

"reward": +1]\}

Few Shot

Figure 22: System prompt for Rubik cube environment Part 2.

```
FUNCTION_STRUCTURE = {
 "name": "getReward",
  "parameters": {
   "type": "object",
   "properties": {
    "states": {
      "type": "array",
      "items": {
       "type": "object",
       "properties": {
        "state": {
         "type": "array",
         "description": "A 3x3 grid representing the state of the board. Each subarray corresponds to a row from left to
                         right, with the first subarray representing the top row, the second representing the middle
                         row, and the third representing the bottom row.",
                   "items": {
          "type": "array",
          "items": {
           "type": "string",
            "enum": ["W", "G", "O", "B", "R", "Y"]
          },
          "minItems": 3,
         "maxItems": 3
         },
         "minItems": 3,
         "maxItems": 3
        },
        "reward": {
         "type": "integer",
         "enum": [1, -1]
        }
      },
       "required": ["state", "reward"]
      }
     }
   },
   "required": ["states"]
 }
}
```

Figure 23: Function calling to force output format in Rubik cube environment.